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The Contribution of Lean Management—Industry 4.0 Technologies to Improving Energy Efficiency

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Abstract: The current socio-economic and environmental context obliges companies to increase their energy efficiency to be competitive, and the development of Industry 4.0 technologies should contribute to improve it. This article analyses the influence of Industry 4.0 technologies on energy efficiency and the mediation of quality management of production process variables. After a descriptive analysis, a correlation and regression analysis is presented using information from 72 projects for the integration of Industry 4.0 technologies in industrial companies. At a global level, it is confirmed that the four technology groups (Artificial Vision and Artificial Intelligence, Additive Manufacturing and Robotics, Big Data and Advanced Analytics, and Internet of Things) contribute to improving energy efficiency by an average of 15–25% in the processes where they are integrated. In addition, the regression model determines that improved decision-making capabilities strongly mediate the achievement of higher energy efficiency.

Keywords: energy efficiency; Industry 4.0; sustainability; quality management

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1. Introduction

The International Energy Agency points out that the world is in a complex global energy crisis [1]. The World Energy Outlook (WEO) concluded that industries exposed to global energy prices face real threats of rationing and consequently their production could be affected [1]. This situation has triggered governments around the world to act in the face of this energy crisis towards more efficient energy systems. Thus, in 2021 the United Nations identified energy efficiency activities as a priority. The United Nations Environment Programme focuses on research, development, transfer, and promotion of innovative industrial technologies to improve energy efficiency [2]. In the European Union, the European Commission reinforced the European Green Deal [3]. It is linked to the REPowerEU plan for energy saving and diversification of energy supply, and includes the binding target of increasing energy efficiency of production systems to 13% for 2030 [4]. Japan presented the Fifth Science and Technology Basic Plan, aimed at promoting business models with radical technological changes in production, which plays an important role in improving energy efficiency [5,6]. Similarly, China has developed Green Transformation, an initiative whose objective is based on achieving symbiosis between organizations and society using new industrial technology to solve environmental challenges and to achieve energy efficiency and socio-economic growth [7]. In addition, China carried out a strategic plan—Made in China 2025—identifying several priorities: product innovation, productivity improvement, reduction of uncertainty in decision-making and reduction of manufacturing errors, better control of processes, and energy efficiency. It aims to accelerate the ecological transition and promote new information technologies, numerical control tools and robotics, energy-saving vehicles, new energies, and energy equipment, among others [8].

The business world is no stranger to this energy crisis that has become a global threat [9]. To survive, companies must take advantage of the technological opportunities offered by the technological revolution of Industry 4.0 to reduce the consumption of available resources [10]. Additive Manufacturing and Robotics (AMRB), Artificial Vision and Artificial Intelligence (AVAI), Big Data and Advanced Analytics (BDAA), and the Internet of Things (IoT), among other Industry 4.0 technologies, should also serve to minimise energy consumption [11]. In this regard, in 2019 at the World Economic Forum [12], the leading companies in the global digital transformation stated that the impact of Industry 4.0 technologies significantly improves business value and contributes to energy optimisation. Later, in the same vein, the European Economic and Social Committee [13] stated that digital transformation has discovered methods to reduce energy consumption without sacrificing productivity and innovation. It is precisely these two variables, together with others identified in the literature and set out in Section 2 of the paper, that are key to managing the quality management of production process variables and ultimately the competitiveness and sustainability of companies. Therefore, by articulating strategies to improve the values of these variables (mediating variables) with the support of new Industry 4.0 technologies, we can expect to improve energy efficiency in the production processes of industrial companies. Although the relationship between the integration of Industry 4.0 technologies and the energy efficiency of processes in companies has been extensively studied [14,15], the present research improves the understanding of what this interrelationship looks like. Using variables widely used in quality management and production process innovation, we have determined how these variables affect energy efficiency in the adoption of Industry 4.0 technologies. Company managers and technicians are very familiar with these quality management variables, and they largely determine energy performance in industrial companies. Managing these processes requires knowledge of the key variables that influence many aspects of company performance, including energy efficiency [14].

This knowledge can be especially useful for industrial companies interested in integrating new Industry 4.0 technologies in the design of strategies. The paper is organised as follows. The following section presents the literature review, followed by the methodological section, results and conclusions.

2. Literature Review

Academic literature highlights the increasing role of digital technologies towards an energy efficient society [16] and their adaptation to different industrial sectors through different Industry 4.0 technologies [17]. Sajadieh et al. [18] and Bermeo-Ayerve et al. [19] add that smart factories must also be energy efficient to achieve global competitiveness with technological solutions. Some authors point out that the combined use of Industry 4.0 technologies offers potential to reduce production waste, overproduction and goods movement and contribute to minimising energy consumption [20,21]. For example, AMRB together with BDAA and cloud manufacturing factors in production systems contribute to increase efficiency in energy use [11]. Intelligent energy management analysis of various systems through BDAA can improve predictive control, reduce energy intensity, and generate a reduction in energy consumption [22]. The literature also notes that BDAA and AMRB facilitate value creation and energy efficiency in distribution and supply chains [23–25].

However, the implementation of Industry 4.0 technologies in industry must be approached from the perspective of operational performance of quality management variables of production processes along with those of innovation management [26,27]. In the literature, studies highlight the relationship of some of the main variables, such as productivity, manufacturing errors, product innovation, decision-making and process control, linked to energy efficiency [28–32]:

- Productivity: The ratio of economic output per unit of energy use has been a common metric used to measure relative performance in interrelated economic, energy and environmental issues [33]. Today, it is possible to identify energy-consuming processes, through the production process, and measure energy efficiency [34], since the main factors responsible for energy efficiency in industrial companies are related mainly to production activities [35]. Many analyses have referred to the industrial productivity benefits associated with energy efficiency [36]. Zhang et al. [6] assert the need to adjust the dispersion of labour productivity, optimise energy investment activities, strengthen energy price control mechanisms and energy intensity to improve energy efficiency and energy cost. The configuration of Industry 4.0 technologies and their integration into the production process favours efficient production, improving productivity and efficient use of resources and energy [37]. One example is IoT technology, which enables the control of energy savings [38,39] through intelligent energy analysis. Another example is BDAA, which serves to implement real-time monitoring methods, developing optimisation algorithms, and controlling all devices with precision for flexibility of manufacturing resources to achieve productivity gains [40].
- Manufacturing errors: Saez et al. [31] highlight that efforts to improve the integration of Industry 4.0 technologies into manufacturing operations and reduce manufacturing errors must be part of a holistic approach that considers other aspects, such as energy efficiency [31]. Therefore, companies have incorporated maintenance and production scheduling practices to avoid manufacturing errors and control energy efficiency [41]. In addition, [42] propose the development of models that early error detection can reduce energy consumption by turning machines on/off and pausing their operation.
- Product innovation: Improved energy efficiency and more specifically reduced energy consumption can occur as a side effect of actual product and process innovation activities [43–45]. In fact, Liang et al. [46] points out that, at present, enterprises in industrial clusters promote the development of innovative products, processes, and technologies to achieve an energy-saving effect. In addition, green product and process innovation are presented as the economic development pattern of enterprises to conserve generate, transform, and make efficient use of energy [32,35,47]. In this way, it will not only contribute to increasing economic output but will also have an impact on facilitating energy demand management [48].
- Decision-making: Among the quality variables of production processes, uncertainty in decision-making is reduced by monitoring energy, equipment, reliability, real-time quality, and multi-criteria decision-making methods [49,50]. Nowadays, most energy solutions are carried out by genetic algorithms with the help of AVAI technology through energy performance analysis, load prediction, anomaly detection, and consumption pattern recognition to support decision-making [51] and reach optimal solutions. On the other hand, the integration of BDAA with AVAI provides greater operational advantage to enterprises [52] and contributes to decision support, product and process innovation, and risk mitigation.
- Process control: This requires advanced continuous monitoring technologies for smart management of both consumers and producers in relation to energy distribution on different scales: from a single appliance to an entire building or even at the village and city level [53]. Thus, among the most relevant consequences of the adoption at machine level are the implementation of control strategies for the efficient use of components and the minimisation of processing time and non-value tasks, such as reducing the energy demand of machines during idle periods [54]. Monitoring and controlling machines can reduce their energy consumption [31].

The aim of our research is to show how companies can benefit from Industry 4.0-related technologies and consequently improve their energy performance. We have approached this question by looking at classical quality management variables used in production processes, with which company managers and technicians are perfectly familiar.

Therefore, based on the literature review, shown in Table 1, and the stated objectives of our research, we pose the following research questions (RQ):

- RQ1: What is the influence of Industry 4.0 technologies on the variables usually involved in the quality management of production processes?
- RQ2: What is the influence of Industry 4.0 technologies on energy efficiency?
- RQ3: What is the mediation of quality management of production process variables on energy efficiency in the adoption of Industry 4.0 technologies?

Table 1. Literature review.

[Ref.] Authors (Year)	Research Gap	Methodology-Data	Main Contributions
[23] Witkowski (2017)	Innovation in production logistics with Industry 4.0 technologies	Analysis of 900 strategic, inter-company and high value innovation projects from Europe, USA and China	Industry 4.0 technologies contribute to technical and technological product innovation.
[20] Kamble et al. (2018)	Sustainability of Industry 4.0 technologies based on process integration, process control, innovation and product quality	Literature review of 85 papers	Industry 4.0 contributes to sustainable benefits, process safety, energy efficiency and productivity, energy generation and distribution.
[40] da Silva et al. (2020)	Industry 4.0 technologies for improving productivity, smart factory performance and production, self-decision, and machine control	Literature review of 2519 papers	The combination of Industry 4.0 technologies and cloud computing are necessary to process data related to consumption, savings, and energy efficiency.
[14] Urban et al. (2020)	Possibilities of applying Industry 4.0 concepts and tools to the product development process.	Single case study	Innovations based on AR/VR technologies optimize energy efficiency up to 30%.
[38] Hossein et al. (2020)	Industry 4.0 solutions in the energy sector: Energy supply, transmission, distribution, and energy demand.	Literature review of 168 papers	The IoT in the energy supply chain and the advantages of IoT-based energy management systems increase energy efficiency.
[44] da Rosa et al. (2020)	Product and process innovation in reducing energy consumption.	Analysis of 116,962 companies from 55 sectors.	Innovative products and process innovation leads to a reduction in energy consumption.
[21] Dantas et al. (2021)	Analysis of CE and Industry 4.0 technologies in the contribution to the implementation of sustainable practices of the 2030 Agenda	Literature review of 50 papers	Better process control increases flexibility, production agility and, in turn, organisational agility.
[11] Laskurain-Iturbe et al. (2021)	Influence of Industry 4.0 technologies on the circular economy	Multiple case study of 27 projects of Industry 4.0 technologies	Industry 4.0 technologies offer companies solutions to reduce consumption of energy.Important differences between the potential impacts of each technology.
[25] Zekić-Sušac et al. (2021)	Integration of BD and machine learning into an intelligent system for energy efficiency management	Study of 17,000 public buildings	The combination of AI, BD and IoT show potential for smart energy management and energy efficiency.
[48] Amin et al. (2022)	Energy consumption, energy productivity and eco-innovation	Data available from 1995 to 2019	The use of advanced technology increases energy productivity and in turn reduces consumption.
[51] Chen et al. (2022)	Reducing uncertainty in decision making, reduce uncertainty and achieve energy efficiency.	19,725,379-energy performance of buildings data records.	Increased use of machines based on predictive processes contributes to less uncertainty at the start of energy efficient design.
[52] Hajiagha et al. (2022)	Benefits of Industry 4.0 technologies for decision making	12 experts participated with the DEMATEL (Decision Making Trial and Evaluation Laboratory) methodology.	Industry 4.0 technologies contribute to operational excellence, continuously improving processes to achieve optimal performance, and improving the energy efficiency of equipment and machinery.
[34] Khraiche et al. (2022)	Energy efficiency policies and targets.	Study of 44 countries in Europe from 1990 to 2015	Between 1999 and 2015, most European countries experienced a reduction in energy efficiency as the adoption of technology involved
[16] Neligan et al. (2022)	Digitization as a potential force towards the circularity of products and more energy efficient	Multiple case study: 599 manufacturing companies and 296 industrial service providers.	Companies improve resource efficiency at different stages of a product's life cycle by: driving innovation, digitisation and circularity together with financial analysis.
[18] Sajadieh et al. (2022)	Manufacturing paradigm of smart factory technologies and urban manufacturing	Multiple case study: 9 smart factories.	Conceptual definition of urban smart factory (SF): A human-centric factory with four pillars: personalization, sustainability, resilience, and SF.

3. Research Methodology

3.1. Sample Frame and Variables

The study took as a reference the Industry 4.0 technology adoption projects presented in the first four editions of the BIND 4.0 programme, which specialises in promoting Industry 4.0 projects. BIND 4.0 won the European Enterprise Promotion Awards 2020 (EEPA) in the category "Improving the business environment" [55]. Within the 168 projects submitted, 130 projects were pre-analysed and companies initially contacted via email. Subsequently, 72 projects developed by 63 companies from Europe, America, Asia, and Africa were selected and analysed in depth. These projects were representative of manufacturers of technological products or services with applications in the fields of advanced manufacturing, smart energy, transport, and telecommunications, among others, which provided innovations and for which it was possible to obtain verified information from different sources. They had to be informative cases with accessible access to evidence, answer the research questions and achieve a minimum representation of the technology groups [56]. In a first step, the projects were classified by 8 technological categories, taking into account the classification used by SPRI (the Basque public agency for business development, precursor of the BIND 4.0 programme) (SPRI, 2017). However, they were subsequently grouped into four majors Industry 4.0 technology clusters, as most of the projects integrated technology clusters. In addition, the technology clusters were required to have a minimum of representativeness of 4 or more projects) [57]. Finally, 11 projects on AMRB, 24 AVAI, 16 BDAA and 21 IoT were analysed. A short description of each project and the main source of evidence in each case is presented in Table 2 (please note that other sources and tools have been used, such as email, which is very useful to resolve issues that are not perfectly clear or to corroborate/reject some evidence).

Table 2. Description of the selected projects and the sources of data collection used.

Technology—Industry 4.0 Project	Source of Evidence †
AMRB 1—Design and manufacture of complex metal parts for the automotive industry.	I(1)/V(2)/D(15)
AMRB 2—Obtain 3D models of a very specific piece used in an oil refinery.	I(3)/V(0)/D(7)
AMRB 3—Development of thermoplastic automotive components.	I(1)/V(1)/D(7)
AMRB 4—3D printing software that corrects anisotropy.	I(1)/V(1)/D(4)
AMRB 5—Development of new AM tools for industrial processes and metallic aeronautical components assembly.	I(1)/V(0)/D(3)
AMRB 6—Manufacture of prototypes for its geometric, dimensional, mechanical and structural validation.	I(2)/V(0)/D(6)
AMRB 7—Metal AM in manufacturing process.	I(1)/V(1)/D(7)
AMRB 8—Surface treatments to avoid light transmission losses in optical measuring equipment in aggressive environments.	I(2)/V(1)/D(3)
AMRB 9—Technological scouting on AM technologies.	I(1)/V(1)/D(7)
AMRB 10—Design and manufacture of 3D metal printers based on SLM technology.	I(2)/V(1)/D(5)
AMRB 11—Design, manufacture and produce custom, trustworthy & connected 3D printers.	I(2)/V(0)/D(6)
AVAI 1—Robot for predictive maintenance improvement in automotive sector.	I(1)/V(2)/D(4)
AVAI 2—Development and construction of an AV prototype for non-contact measurement of sheet thickness in areas susceptible to stretch-type defects.	I(1)/V(2)/D(7)
AVAI 3—Sheet metal quality control in assembly process.	I(2)/V(1)/D(14)
AVAI 4—Development of an automatic and continuous arrow measurement system with artificial vision.	I(3)/V(1)/D(7)
AVAI 5—Process compliance control in manual position.	I(2)/V(0)/D(10)

Table 2. *Cont.*

Technology—Industry 4.0 Project	Source of Evidence †
AVAI 6—AI algorithms to reduce energy consumption of industrial plants.	I(2)/V(0)/D(5)
AVAI 7—Recognition of broken machines using sound.	I(1)/V(0)/D(6)
AVAI 8—Digital transformation into business opportunities.	I(1)/V(0)/D(5)
AVAI 9—Improve the energy management in buildings with high savings and comfort levels.	I(2)/V(0)/D(3)
AVAI 10—AI prototyping for non-contact measurement of sheet thickness in areas susceptible to stretch-type defects	I(1)/V(1)/D(6)
AVAI 11—Sheet metal quality control in assembly process.	I(3)/V(1)/D(4)
AVAI 12—Development of an automatic and continuous arrow measurement system with artificial vision.	I(2)/V(1)/D(5)
AVAI 13—Process compliance control in manual position.	I(2)/V(1)/D(6)
AVAI 14—AI algorithms to reduce energy consumption of industrial plants.	I(1)/V(1)/D(6)
AVAI 15—Intelligent reading of consumption meters, for the extraction of different fields of interest from an image through mobile devices.	I(3)/V(1)/D(7)
AVAI 16—AI-powered HMI and assistant to augment workers in the digital factory.	I(2)/V(0)/D(6)
AVAI 17—Industrial AI solutions for transforming process data into value.	I(3)/V(2)/D(5)
AVAI 18—Replacing manned helicopters with long-range drones.	I(2)/V(1)/D(4)
AVAI 19—Build a predictive machine failure analytics model based on the Halerium tool.	I(2)/V(2)/D(7)
AVAI 20—Data analysis via AI algorithms in converters for preventive maintenance, sizing of components, calculating operational limit	I(1)/V(0)/D(3)
AVAI 21—Robotic process automation through the development and design of interfaces based on AI.	I(3)/V(0)/D(7)
AVAI 22—Simplify complex processes and automate what required humans with help of natural language processing and AI.	I(2)/V(2)/D(6)
AVAI 23—Personal data anonymization software based on AI.	I(1)/V(1)/D(3)
AVAI 24—Digitising the most distributed infrastructure on earth, power lines.	I(3)/V(0)/D(4)
BDAA 1—Help automotive companies to make smart decisions based on their own data.	I(3)/V(2)/D(7)
BDAA 2—Identify patterns of behaviour in telecom operator's mobile customers in order to optimize investments in its network.	I(2)/V(1)/D(4)
BDAA 3—Big data and machine learning to chrome plated processes at auto parts manufacturer.	I(3)/V(0)/D(5)
BDAA 4—Optimize manufacturing processes at airplane engines manufacturer.	I(2)/V(0)/D(7)
BDAA 5—Data analytics project aimed at creating value for operator's customers.	I(3)/V(2)/D(6)
BDAA 6—Analysis of the vegetation around electrical infrastructure using nanosatellites images.	I(2)/V(0)/D(3)
BDAA 7—Special programming of the Berckhoff automation tool in order to acquire the capacity of introduce owned models.	I(1)/V(2)/D(6)
BDAA 8—Warehouse management optimization.	I(2)/V(2)/D(5)
BDAA 9—Validation of approximation through neural networks to Recovery Time Objective in process units.	I(1)/V(1)/D(5)
BDAA 10—Modelling and optimization of manufacturing processes based on advanced analytical techniques.	I(3)/V(0)/D(4)
BDAA 11—Sensorization pilot project to validate the potential and maturity of the technology.	I(1)/V(0)/D(3)
BDAA 12—Transform data captured from multiple sources (SCADA, ERP, BI) into valuable information for decision making.	I(3)/V(0)/D(6)
BDAA 13—Asset health information platform for early detection of component defects that cause failures.	I(2)/V(1)/D(3)

Table 2. *Cont.*

Technology—Industry 4.0 Project	Source of Evidence †
BDAA 14—Implementation of an intelligent system for production planning.	I(1)/V(0)/D(5)
BDAA 15—Software platform to connect safely machines, data and analysis for operating efficiency.	I(2)/V(0)/D(5)
BDAA 16—Implementation of a technological infrastructure that allows relating process parameters with results in the product.	I(1)/V(2)/D(4)
IOT 1—Operational intelligence for wind turbines, met masts, solar plants and IoT devices.	I(1)/V(0)/D(6)
IOT 2—Help clients build their own devices by connecting them with sensors and wireless communicators.	I(1)/V(1)/D (6)
IOT 3—Oil circuit monitoring solution for compressors and hydraulic systems (lifting table) in automotive sector.	I(3)/V(2)/D(4)
IOT 4—Cloud platform to monitor and control company processes.	I(1)/V(1)/D(3)
IOT 5—Predictive maintenance of infrastructures based on a scalable assistance system.	I(3)/V(1)/D(6)
IOT 6—Project focused on the asset management field.	I(3)/V(0)/D(5)
IOT 7—Optimising preventive maintenance of a cable-processing machine.	I (2)/V(1)/D(6)
IOT 8—Connection, control and management of the forming machinery area and its possible connection with the current ERP.	I(2)/V(0)/D(7)
IOT 9—Automatic output record of measurement equipment and tools from the warehouse with RFID technology.	I(1)/V(1)/D(5)
IOT 10—Workers' safety system, capable of detecting falls. Risk assessment of different jobs.	I(2)/V(2)/D(4)
IOT 11—Ergonomic evaluation in real time.	I(3)/V(1)/D(3)
IOT 12—Monitoring of production cells in industrial plants.	I(2)/V(1)/D(7)
IOT 13—Management of the push bench gearboxes for controlling aspects like the assembly of them in the bench or the tones laminated by each one.	I(2)/V(2)/D(5)
IOT 14—Industrial asset tracking and forklift fleet analytics.	I(2)/V(1)/D(3)
IOT 15—Development of software solution for automation systems.	I(1)/V(2)/D(6)
IOT 16—VCSim simulation tool in a set of distributed and interconnected parts.	I(2)/V(0)/D(7)
IOT 17—Indoor geolocation and analysis of industrial assets.	I(2)/V(2)/D(4)
IOT 18—Monitoring any parameter in energy-intensive industry easily and costly-effectively using waste heat as a source of energy.	I(3)/V(0)/D(4)
IOT 19—Surface treatments to avoid light transmission losses in optical measuring equipment in aggressive environments.	I(3)/V(0)/D(4)
IOT 20—Implementation of corporate electric mobility solutions.	I(1)/V(1)/D(6)
IOT 21—Process automation & asset digitalization through RFID.	I(1)/V(1)/D(4)

Note: † I, interviews; V, visits; D, document analysis.

Table 3 describes the three groups of variables analysed for this study. In an attempt to limit subjectivity, for each variable 72 values were measured using three main sources of data collection for each project, as mentioned before: interviews, visits and document analysis. Negative influences were not detected in the study, so they have not been included.

Table 3. Classification of variables measured in the study.

Group	Variable	Type	Scale
Industry 4.0 Technologies	AMRB AVAI BDAA IoT	Dummy	0 = No 1 = Yes
Quality management of production processes	Productivity Manufacturing errors Product innovation Decision-making Process control	Likert	0 = No influence 1 = Very little influence 2 = Little influence 3 = Medium influence 4 = High influence 5 = Very high influence
Energy efficiency	Energy efficiency	Likert	0 = No influence 1 = Improv. less than 5% 2 = Improv. between 5–10% 3 = Improv. between 15–20% 4 = Improv. between 20–25% 5 = Improv. more than 25%

3.2. Qualitative Approach

Qualitative techniques and methodologies have been used in this research for several reasons. The use of qualitative methods allows for a considerable increase in knowledge about the behaviour of organisations, and among all of them, the case study allows for generating a very important level of realism in the conclusions of the research [58], which it is precisely the point in this research. Instead of one, a multiple case study was conducted to reinforce the analytical generalisations with corroborated evidence (literal replication), which is essential to provide the research with internal validity.

The case study methodology allows the phenomenon to be analysed in its real context, considering all aspects of the problem, and using multiple sources of evidence, quantitative and/or qualitative simultaneously [59]. It is worth clarifying that certain methodologies considered qualitative, such as case studies, do not only handle qualitative information, as the same case study can contain both qualitative and quantitative information [57]. Case study research allows the use of either qualitative data exclusively or quantitative data exclusively, or even both [56,57]. Moreover, it is possible to combine qualitative and quantitative methods so that a set of hypotheses can be generated from the application of qualitative instruments and then tested quantitatively [58,60].

In Table 4, key elements of the research protocol are highlighted. Evidence was collected through passive and active observation (methodological triangulation) [57]. In accordance with the principle of data saturation [61], data collection was interrupted when no new themes emerged that could enrich the existing results, and documents such as project reports or technical reports were collected for analysis (data triangulation). The evidence collected was then examined, categorised, tabulated, and reviewed, seeking to identify common patterns of behaviour across cases and determine the connection between the data and the research objectives [62].

Table 4. Measures taken to ensure the validity and reliability of the case study.

	Research Phase			
	Design	**Case Selection**	**Data Collection**	**Data Analysis**
Reliability	Develop case study protocols based on the literature.	Selection based on theoretical sampling (Yin, 2017).	Provide the script to all interviewees prior to the interview. Develop a case study database (with all available documents: interview transcripts, archives, etc.) (Lincoln and Guba, 1985).	Third-party review of the processes followed in the research process (Lincoln and Guba, 1985).
Internal validity	Establish the theoretical framework prior to data analysis (Eisenhardt, 1989; Yin, 2017).	Sampling criteria in the case study protocol (Yin, 2017).	Records of factors that could serve as alternative explanations (Miles et al., 2018)	Pattern matching (matching patterns identified in the work of other authors) (Miles et al., 2018). Triangulation techniques: multiple sources of evidence and data collection methods (Lincoln and Guba, 1985).
Construct validity	The use of multiple sources of evidence: interviews, documents, artefacts and others, to protect against researcher bias (Flick, 1992; Peräkylä, 1997).	N/A	Peer review of transcripts and drafts (LeCompte and Goetz, 1982).	Chain of evidence (verbatim transcripts of interviews and notes from company observations to cross-check data from particular sources of evidence) (Griggs 1987; Hirschman, 1986). Let key informants and other supporting researchers review the data analysis and the draft report findings (Yin, 2017).
External validity	Justification for the selection of case studies. Defining the scope and limits at the research design stage (Marshall and Rossman, 1989).	Description of business cases and contextual factors of the case study (Yin, 2017).	N/A	Not Applicable

3.3. *Quantitative Approach*

Finally, the research questions were tested with the quantitative studies. The statistical software SPSS v28 was used for this purpose. Initially, a descriptive study was carried out based on the results obtained in the qualitative analysis. We calculated the means and variances of the quality management of production processes variables and the energy efficiency. Using the Kruskal–Wallis test, we analysed if there were significance differences between the results obtained for the different technology groups for these six variables. In the second analysis, a correlation analysis between the variables of quality management of production process and the energy efficiency was conducted [63].

Finally, prior to the model-type selection, the common method bias was analysed using Harman's post hoc single-factor test for the quality management variables of the production processes. The factor with the greatest weight, 43.155%, was lower than the 50% recommended in the literature [64]. In addition, a dimension reduction analysis was conducted. In this analysis, the need was identified to represent the quality management variables of the production processes by means of two components. The first component included the variables “productivity”, “manufacturing errors”, “decision-making”, and “process control” and the second “product innovation”. To test its construct validity, a factor analysis was carried out. The construct can be considered unifactorial because the percentage of variance associated with the first component of this group of variables was 59.12%, with lower values for the rest of the components [65]. To test its internal consistency, a reliability test was carried out using Cronbach’s α as a statistic. To pass this test, a value of over 0.7 is considered advisable [66]. In this study, the construct had an indicator value of 0.758, meaning that the data had suitable internal consistency. In the collinearity analysis, the IoT variable was also eliminated due to the degree of collinearity with the other three technology groups [67].

In order to select the model, the variance explained by the model calculated by the R^2 indicator and the significance of the model were considered. In this selection process, it was observed that the linear regression model without constant explained more than 62% of the variance including only the Industry 4.0 technologies and 83% once the components representing the quality variables of the production processes were inserted. Moreover, it allowed F values always higher than 40, so that the models were significant for alpha = 0.01. For these reasons, taking into account the recommendations indicated in the literature [63], it was considered that this model performed in two steps was optimally suited to the object of the study and allowed us to analyse the influence of the set of Industry 4.0 technologies on energy efficiency, considering the mediation of the quality management variables of the production process. The equations of the model were:

In the first step,

$$\text{Energy efficiency} = \beta_{11} \times \text{AMRB} + \beta_{12} \times \text{AVAI} + \beta_{13} \times \text{BDAA} + \text{error} \quad (1)$$

In the second step,

$$\text{Energy efficiency} = \beta_{21} \times \text{AMRB} + \beta_{22} \times \text{AVAI} + \beta_{23} \times \text{BDAA} + \beta_{24} \times \text{product innovation} + \beta_{25} \times \text{decision-making} + \text{error} \quad (2)$$

Afterwards, four two-step regression analyses were run, including within the technology part each of the individual technologies, to find out whether there were differences in the measurement of the different technology groups.

Finally, four two-step regression analyses were carried out, including each technology individually within the technology part, to find out whether there were differences in the mediation of the different technology groups.

4. Results

The research focused on the study of technology companies that have combined several of the technologies AMRB, AVAI, BDAA, and IoT to clarify unresolved issues, and to reinforce or even reject the previous conclusions of the literature. The main sources of evidence were internal documents (real cases, applications, reports, memories of Industry 4.0 projects, etc.) and direct communication with managers and technicians [68]. The visits made it possible to study the influence of energy efficiency, analysing how the integration of Industry 4.0 technologies influences on the variables of quality management of the production processes: productivity, manufacturing error, product innovation, decision-making and process control, together with the influence of these on energy consumption. Among the results, the documentation provided by managers and technicians was examined.

4.1. Influence of the Integration of Industry 4.0 Technologies on the Quality Management of Production Processes

In a first analysis, after examining, categorising, tabulating, reviewing the evidence, and identifying common patterns of behaviour, the connection between quality management of production processes variables and Industry 4.0 technologies was determined.

Figure 1 shows graphically the influence of Industry 4.0 technologies on the variables analysed. The statistical results show a positive influence (from 2.5 to 3.49), high positive (from 3.5 to 4.49), and very high positive (from 4.5 to 5) between the adoption of AMRB, AVAI, BDAA and IoT technologies and the quality management of production processes variables (productivity, manufacturing errors, product innovation, decision-making, and process control). It is observed that the adoption of Industry 4.0 technologies increases productivity, improves product innovation and process control, and reduces manufacturing errors and uncertainty in decision-making. Using the Kruskal–Wallis test, significant differences were not detected between the four technology groups. The managers remarked that these influences depend on the type of technologies, the type of processes, and how the technologies are adopted, but in this study, in terms of type of technology, significant differences were not detected.

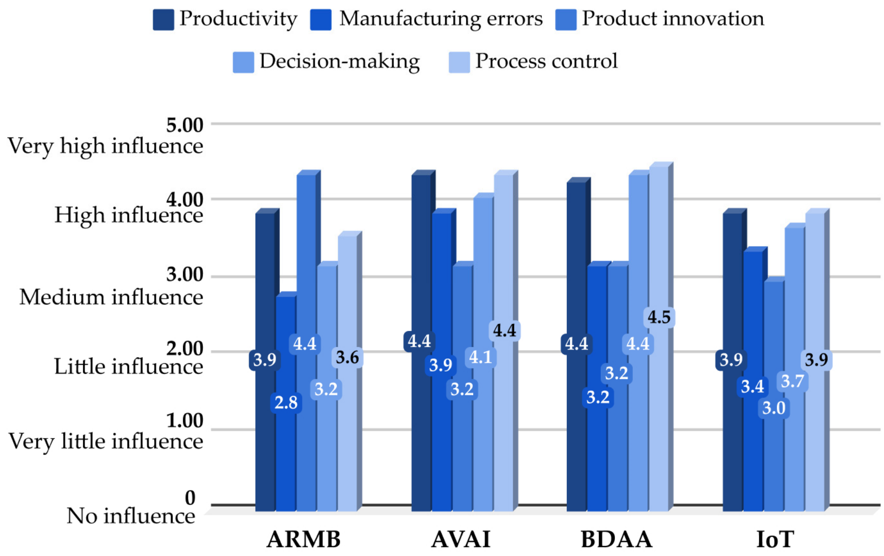

Figure 1. Influence of the adoption of Industry 4.0 technologies on the quality management of production processes. Note: The calculation is based on the average of the influence of each technology in relation to the quality management of production process variables.

Thus, the combination of AMRB technologies achieves a very high positive influence on product innovation. As an example, a technical supplier to the aeronautic industry said that some parts that used to be made by assembling more than 10 components in several stages, with AMRB integration are now made in one single stage, without components or welding, which opens a wide range of possible new product innovations at an affordable price. As it was observed in the case studies and stated in the literature [69,70], due to the difficult task of integrating and managing innovation in the processes, the need for resources and efforts to produce new knowledge in the production process is very high. The managers added that this aspect influences negatively at the first stage on the manufacturing errors. However, even if it is the technology group with the lowest value obtained on manufacturing errors, the influence in the long term is considered positive.

The combination of AVAI and BDAA technologies achieved a very high positive result. Among the results, AVAI technology achieved very high positive results in relation to productivity, decision-making and process control and BDAA technology in product productivity, decision-making and process control. In this sense, several managers highlighted the wide range of information capture and processing that these technologies create. This is linked to greater "process control", earlier detection of "manufacturing errors", and more "decision-making" tools. In relation to IoT technology, the results show a medium–high positive influence on all of the variables.

4.2. Influence of the Integration of Industry 4.0 Technologies on Energy Efficiency

All technologies have a positive or high positive influence on energy efficiency with values that vary from 3.00 AMRB to 3.56 AVAI, but using the Kruskal–Wallis test, significant differences were not detected between the four technology groups. This means that in the processes or sub-processes where they are applied, on average energy efficiency improves by 15% to 25% in the four technology groups. However, as the managers pointed out, the percentage of improvement depends largely on the initial situation, the type of process, and in some cases, such as AMRB, on the batch size. They consider that the level of efficiency is very high for small batch sizes, in some cases up to 70% (aerospace industry application), and lower as the size of the batch increases (suppliers of automotive and lift manufacturing industry) with improvements between the 2% and 5%. This fact was explained by a technician working for a company supplier of the automotive industry, who stated that "for the preparation of prototypes, this technology required mainly programming activities, but traditional technologies required much more work and energy consumption in machine preparation and adjustment tasks".

With regard to AVAI, the technicians pointed out that AVAI are very useful for applying continuous improvement actions because AVAI allow them to work with more information in the processes. For this reason, they consider that "the greater the experience of working with these technologies, the greater the accumulation of improvements in relation to energy efficiency".

Therefore, Industry 4.0 technologies offer opportunities to improve energy efficiency. However, despite the fact that no significant differences were detected in the quantitative statistical analysis, as pointed out by a manager of a company that manufactured large electric motors, "the selection of the technology in which to invest must be made with great care". The characteristics of the range of parts to be manufactured, their variability in terms of quantity and characteristics, and their integration with respect to the rest of the processes must be taken into account. In this respect, he explained how the vibrations in the workshop led them to need a new distribution of spaces, as they had an impact on the non-compliance of specifications of parts manufactured with AMRB.

4.3. Correlation Analysis between Quality Management of Production Processes Variables and Energy Consumption

In this section, we analyse the linear relationship between the quality management variables of the production processes and energy efficiency. Table 5 shows that the quality management variables that measure productivity, manufacturing errors, decision-making and process control have a positive significant linear relationship with respect to consumption of energy per product manufactured. However, the product innovation variable has a negligible correlation value, and therefore no linear relationship can be considered to exist. In this respect, several technicians and managers highlighted the relationship between the variables of quality management of production processes analysed. In a project involving AVAI, its managers explained the reasons of this relationship and the correlation. They emphasized that "(having) more data in the company's information system on the processes improved decision-making and allowed for greater control of the processes". These aspects affect a reduction in manufacturing errors. Moreover, when they did appear, action could be taken more quickly because they were detected earlier and there was more information about their causes. Furthermore, they added that all of this had an impact on the application of improvement actions that improve the productivity and the energy efficiency.

Table 5. Pearson correlation indices of quality management of production process variables with energy efficiency.

		Productivity	**Manufacturing Errors**	**Product Innovation**	**Decision Making**	**Process Control**
Energy efficiency	Index	0.249	0.229	−0.060	0.314	0.371
	Sig.	0.035	0.053	0.617	0.007	0.001

4.4. Mediation of Quality Management of Production Processes Variables on the Influence of the Adoption of Industry 4.0 Technologies on Energy Efficiency

This section presents a multiple regression analysis including the technologies used as dummy-code variables, and the mediation of the quality management of production process variables on energy efficiency. As has been stated previously, a factorial analysis was carried out using the principal component analysis method. In the test, it was observed that the variables "Improvement in product innovation" (extraction factor 0.905) and "Reduction of uncertainty in decision-making" (extraction factor 0.890) accumulated 70.4% of the variance, so these two variables were integrated together with the variables of belonging to one or other technology within the multiple regression model. A deeper factor analysis shows that the variable "Reduction of uncertainty in decision-making" shares the 59.12% of the variance with the variables "Productivity", "Manufacturing errors" and "Process control" and is the most representative of this set of quality management of production processes variables. In the collinearity analysis, the IoT variable was also eliminated due to the degree of collinearity with the other three technology groups.

The regression model was integrated without a constant to maximize the explained variance. It has been developed in two steps. In the first step, the overall influence of AMRB, AVAI and BDAA on energy efficiency was analysed without including the quality management of production processes variables. In the second step, the quality management of production process variables was included in the model.

As a result, in both cases the model was significant at $\alpha = 0.001$. In the second step, the significance increased: the F value increased from 40.674 to 75.221. In addition, the R^2 value has increased from 0.623 to 0.838, so the percentage of the variance explained in the second step by the model is 83.8%. This value is considered optimum in the literature [63].

As a result, the multiple linear regression models are explained by the following equations, being the standard error of the model's estimation 2.13 in the first step and 1.4.

As can be seen in Table 6, in the first step the three technologies are significant at $\alpha = 0.001$. However, in the second step, the only significant variable that appears in the model is the production process quality management variable called "decision-making" with a linear influence value of 0.761. In addition, the value indicates that the linear relation is positive and strong. For this reason, this result confirms the great importance of the mediation of the variable in the process of adopting Industry 4.0 technologies to reduce energy consumption, as can be seen in the equations.

Table 6. Multiple regression model.

Step	Model Information				AMRB		AVAI		BDAA		Product Innovation		Decision-Making	
	R^2	F	Sig.	Error	β	Sig.	β	Sig.	β	Sig.	β	Sig.	B	Sig.
1st	0.623	40.674	<0.001	2.13	0.343	<0.001	0.536	<0.001	0.483	<0.001	-	-	-	-
2nd	0.838	75.221	<0.001	1.4	0.096	0.122	0.056	0.425	0.073	0.258	0.064	0.607	0.761	<0.001

In the first step,

$$\text{Energy efficiency} = (0.343\,^{\dagger}) \times \text{AMRB} + (0.536\,^{\dagger}) \times \text{AVAI} + (0.483\,^{\dagger}) \times \text{BDAA} + \text{error} \tag{3}$$

In the second step,

$$\text{Energy efficiency} = 0.096 \times \text{AMRB} + 0.056 \times \text{AVAI} + 0.073 \times \text{BDAA} + 0.064 \times \text{product innovation} + (0.761\,^{\dagger}) \times \text{decision making} + \text{error} \tag{4}$$

Furthermore, the technical experts agreed that the "decision-making" variable contributed to a gradual improvement in energy efficiency after the adoption of Industry 4.0 technologies. These improvements start to accumulate from the beginning, though the degree of improvements achieved decreases over time.

In addition, multiple regression models classified by technology groups were conducted (Table 7). They show that in the first step, even though the R^2 values are very low and vary between 0.118 and 0.277, the technological variables have a significant positive influence on the four technology groups and the models are significant at $\alpha = 0.01$. However, in the second step, R^2 values are optimal and explain more than 83% of the variance due to the influence of the "decision-making" variable [63]. This variable becomes the only significant one ($\alpha = 0.01$), with values of β varying between 0.754 and 0.819, as can be observed in the following equations:

Table 7. Multiple regression models classified by technology groups.

Tech.	Model Information				Industry 4.0 Technology		Product Innovation		Decision-Making	
	R^2	F	Sig.	Error	β	Sig.	β	Sig.	B	Sig.
1st Step										
AMRB	0.118	9.484	0.003	3.29	0.343	0.003	-	-	-	-
AVAI	0.277	28.617	<0.001	2.95	0.536	0.001	-	-	-	-
BDAA	0.234	21.650	<0.001	3.06	0.483	0.001	-	-	-	-
IoT	0.217	19.734	<0.001	3.09	0.466	0.001	-	-	-	-
2nd Step										
AMRB	0.837	126.041	<0.001	1.39	0.070	0.215	0.085	0.483	0.819	<0.001
AVAI	0.835	122.747	<0.001	1.41	−0.040	0.945	0.155	0.158	0.779	<0.001
BDAA	0.836	123.629	<0.001	1.41	0.036	0.650	0.160	0.145	0.754	<0.001
IoT	0.836	123.322	<0.001	1.41	0.029	0.601	0.152	0.163	0.765	<0.001

In the first step,

$$\text{Energy efficiency} = (0.343\ ^{**}) \times \text{AMRB} + \text{error} \quad (5)$$

$$\text{Energy efficiency} = (0.536\ ^{**}) \times \text{AVAI} + \text{error} \quad (6)$$

$$\text{Energy efficiency} = (0.483\ ^{**}) \times \text{BDAA} + \text{error} \quad (7)$$

$$\text{Energy efficiency} = (0.466\ ^{**}) \times \text{IoT} + \text{error} \quad (8)$$

In the second step,

$$\text{Energy efficiency} = 0.070 \times \text{AMRB} + 0.085 \times \text{product innovation} + (0.819\ ^{**}) \times \text{decision-making} + \text{error} \quad (9)$$

$$\text{Energy efficiency} = -0.040 \times \text{AVAI} + 0.155 \times \text{product innovation} + (0.779\ ^{**}) \times \text{decision-making} + \text{error} \quad (10)$$

$$\text{Energy efficiency} = 0.036 \times \text{BDAA} + 0.160 \times \text{product innovation} + (0.54\ ^{**}) \times \text{decision-making} + \text{error} \quad (11)$$

$$\text{Energy efficiency} = 0.029 \times \text{IoT} + 0.152 \times \text{product innovation} + (0.765\ ^{**}) \times \text{decision-making} + \text{error} \quad (12)$$

This confirms the high degree of importance of the mediation of this variable between the adoption of all of the Industry 4.0 technology groups and energy efficiency. Moreover, it is noteworthy that the degree of linear influence and mediation is very strong.

5. Discussion and Conclusions

This research shows how Industry 4.0 technologies can contribute to energy efficiency and the importance of the mediation of quality management of production process variables. In general, based on the analysis of the literature and the results obtained, we can state that the adoption of Industry 4.0 technologies exerts a positive medium–high influence on energy efficiency. Projects adopting these technologies achieve an average of 15% to 25% improvement in energy efficiency in the processes where they were implemented. Although no significant differences between the different technology groups were detected in the quantitative analysis, in the qualitative phase, differences in how the influences were detected. Their specific applications, the batch size, the time needed to obtain the level of improvements and how are combined with other technologies are key factors that determine the degree of influence.

In general, the reasons of the high level of influence of the four technology groups AMRB, AVAI, BDAA and IoT on energy efficiency are related to greater precision, flexibility, speed and amount of information and/or greater energy efficiency of operations. These results confirm previous findings about the positive influence of AMRB [71–80], BDAA [81,82], AVAI [36,83] and IoT [38,39].

In addition, in a process of transformation of the socio-tecno-economic model, this research confirms that Industry 4.0 adoption helps to improve the indicators of productivity, manufacturing errors, product innovation, uncertainty of decision-making and process control. Moreover, these influences on productivity, manufacturing errors, uncertainty of decision-making and process control exert linear influence and a high mediation level on energy efficiency. Although the influence and mediation of product innovation is not significant, the mediation of these variables should be relevant in the Industry 4.0 revolution for organizations, policymakers and other stakeholders to define their road map in the adoption process of new technologies.

In relation to the limitations of the research, we highlight the problems in obtaining the same information to measure the quality management of production process variables in different kinds of organizations and types of production processes. This has made it difficult to measure the influence of each of the technologies on each variable. Overcoming this difficulty has been complicated, but the process has been very useful for us to go deeper into the projects and complement the qualitative information. It would be interesting to conduct further research to deepen and improve the level of knowledge while taking into consideration the level of experience working with Industry 4.0 technologies and information about how the process of adoption has been. The level of experience seems to influence the value of the analysed variables in a positive way, and some technicians and managers have highlighted the importance of the conditions of the adoption process. Furthermore, the results depend largely on the type of application developed in the projects, so it would be interesting to classify the analysis according to the type of application in different sectors, though this requires sufficient experiences and data.

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Acronyms

AMRB	**Additive Manufacturing and RoBotics**
AVAI	Artificial Vision and Artificial Intelligence
BDAA	Big Data and Advanced Analytics
CE	Circular Economy
EEPA	European Enterprise Promotion Awards
IoT	Internet of Things
OEM	Original Equipment Manufacturer
RQ	Research Question
WEO	World Energy Outlook

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